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Integrated Traffic and Communication Performance Evaluation of an Intelligent Vehicle Infrastructure Integration (VII) System for Online Travel Time Prediction

Yongchang Ma, Mashrur Chowdhury*, Adel Sadek, and Mansoureh Jeihani

Abstract— This paper presents a framework for online highway travel time prediction using traffic measurements that are likely to be available from Vehicle Infrastructure Integration (VII) systems, in which vehicle and infrastructure devices communicate to improve mobility and safety. In the proposed intelligent VII system, two artificial intelligence (AI) paradigms, namely Artificial Neural Networks (ANN) and Support Vector Regression (SVR), are used to determine future travel time based on such information as current travel time, VII-enabled vehicles' flow and density. The development and performance evaluation of the VII-ANN and VII-SVR frameworks, in both of the traffic and communications domains, were conducted, using an integrated simulation platform, for a highway network in Greenville, South Carolina. Specifically, the simulation platform allows for implementing traffic surveillance and management methods in the traffic simulator PARAMICS, and for evaluating different communication protocols and network parameters in the communication network simulator, ns-2. The study's findings reveal that the designed communications system was capable of supporting the travel time prediction functionality. They also demonstrate that the travel time prediction accuracy of the VII-AI framework was superior to a baseline instantaneous travel time prediction algorithm, with the VII-SVR model slightly outperforming the VII-ANN model. Moreover, the VII-AI framework was shown to be capable of performing reasonably well during non-recurrent congestion scenarios, which traditionally have challenged traffic sensor-based highway travel time prediction methods.

Index Terms— Artificial intelligence (AI), Traffic Simulation, Travel time prediction, Vehicle Infrastructure integration (VII)

I. INTRODUCTION

IN the last few years, there has been an increased interest in real-time traffic condition prediction as an approach to positively influencing travelers' departure time and route choice. Travel time, which is easy to understand, has become the most common traffic condition provided to travelers [1, 2]. However, online travel time prediction is not a classic time series problem [3] due to the delay in the availability of previous data quantities (i.e. a vehicle needs to complete its trip before its travel time can be estimated and made available for future predictions). Current practice typically uses either the historical mean travel time or current travel time (as estimated from inductive loop detector and/or traditional Automatic Vehicle Identification (AVI) systems that depend on fixed-location readers for example) as the basis for the predicted travel time in the near future [4]. These methods, however, do not work satisfactorily during congestion. Moreover, the majority of existing travel-time prediction methods, with the exception of AVI systems, uses densely-placed traffic sensors such as traffic cameras and loop detectors to estimate travel time [4]. These sensors are typically placed at a spacing ranging from every half mile to a quarter of a mile. With these methods, travel time is predicted indirectly based upon traffic sensor measurements, such as volume, density and speed, which may introduce additional errors into the travel time prediction. Added to that, existing travel time prediction models do not perform well under the impact of unexpected incidents [1].

The emerging concept of "Vehicle Infrastructure Integration (VII)", in which vehicles and infrastructure equipments will communicate with one another [5], provides an opportunity to directly collect the travel time and other traffic data in a real-time fashion. As envisioned in VII systems, equipping vehicles and roadside infrastructures with wireless communication interfaces will make it possible to constantly sample the travel time, flow, and density of VII-enabled vehicles. Such substantial improvement in the availability and quality of traffic information would in turn improve the performance and capability of travel time prediction systems. For example, it can be expected that VII travel time prediction systems would be capable of accurately predicting travel time, even during non-recurrent congestion scenarios.

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Previous research has primarily focused on the potential of using VII to benefit highway and intersection collision avoidance. Given the feasibility of using automatic vehicle identification (AVI) and probe vehicle techniques for travel time prediction, this paper proposes to use VII for real-time travel time prediction. Additionally, in order to take full advantage of the wealth of data likely to be provided by VII, intelligent algorithms are used to aid in processing the myriad of data generated through the system. Specifically, this research applied two Artificial Intelligence (AI) paradigms, artificial neural networks (ANN) and support vector regression (SVR), for a VII based real-time freeway travel time prediction framework. Following the development of the proposed VII-ANN and VII-SVR framework, this study evaluated the travel time prediction functionality and performance, in both the traffic and communication domains, of the framework in a simulation environment. Since communication effectiveness plays a key role in determining the overall performance of the VII system, the authors used a simulation platform that integrates traffic and communication simulators to facilitate the study [6]. Detailed and realistic simulation of both traffic and communication interaction can assist researchers in testing various functional architecture designs, implementation algorithms, and parameter configurations, eliminating the need for collecting field data after the implementation of a particular system. The use of simulation provides an alternative, as a more affordable evaluation method, to the costly and complex field experiments.

The remaining parts of this paper are organized as follows. Section II reviews the state-of-the-knowledge regarding online travel time prediction methods, computational intelligence, integrated traffic and communication simulators, and VII. Section III describes the research method and the development of the proposed VII-ANN and VII-SVR framework for online highway travel time prediction. Section IV presents the results from a case study designed to evaluate the performance of the proposed framework in a simulation environment. The paper concludes in Section V with a discussion of the important findings, possible limitations of this study, and future research suggestions.

II. LITERATURE REVIEW

A. Online Travel Time Prediction

Depending on the prediction period horizon, the real-time travel time prediction can be categorized into two types: pre-travel and en-route prediction [2]. Pre-travel prediction usually has a prediction horizon of 30-60 minutes. En-route prediction, on the other hand, has a much shorter time horizon (e.g., 0-5 minutes). This paper focuses on the online travel time prediction for en-route travel.

Existing short-term online travel time prediction methods include: (a) simulation based methods (e.g. DYNAMIT [7], DYNASMART [8]); (b) statistical analysis of historical and real-time data (e.g. instantaneous travel time algorithm [9], linear model [10], pattern matching [11]), and (c) AI-based techniques. Simulation-based travel time prediction methods

are generally regarded as accurate and robust, provided that the traffic environment in which they are deployed is similar to that for which they were calibrated. However, the requirements of dynamic Origin-Destination estimation make them computational resource intensive, and complicated to implement and operate. The statistical methods, on the other hand, are relatively simple and easy to implement. They, however, don't work well for congested conditions due to their insufficient consideration of the highly stochastic and complex nature of the traffic network.

Previous studies have reported promising results from the applications of AI in travel time prediction. Among the different AI paradigms used for travel time prediction, feed forward neural networks appear to be the most popular (e.g. [12, 13]). Other ANN topologies have also been used. Van Lint [1], for example, used state-space neural network (SSNN) model to explicitly consider the prediction of travel time in each section to derive the future travel time of the entire network.

While the AI methods for travel time prediction are fairly accurate and computationally efficient, their developments are usually labor intensive and tailored for a specific application [1]. Specifically, the conventional ANN method suffers from the highly nonlinear and non-monotonic function for the real-time travel time prediction problem. Due to this reason, the issues of slow convergence and local optimization can occur when applying feed forward neural network to traffic sensor based travel time prediction model [14]. Two types of treatments have been proposed to overcome this problem: (a) pre-classification [13]; and (b) pre-mapping (e.g., [14]) of the input data. More recently, Wu et al. [15] proposed to use SVR, a relatively new AI paradigm, for short term travel time prediction. Though their inputs included the realized travel time data that would not be available for a real-time application, their work demonstrated that SVR is a promising tool for travel time prediction. Researchers have reported that SVR requires less computational resources, and has greater prediction potential and learning ability compared to other paradigms [15, 16, 17].

B. Support Vector Regression (SVR)

SVR is a member of the Support Vector Machine (SVM) paradigm family, which is based on Statistical Learning Theory (SLT) and the principal of Structural Risk Minimization (SRM) [18, 19]. SVM algorithms include a suite of supervised machine learning algorithms that are applicable to classification (e.g. two-class Support Vector Classification (SVC), multi-class SVC) as well as regression problems (e.g. SVR). They use kernel functions to map the input data into a high dimensional feature space where linear classification becomes feasible. Since the kernel mapping is implicit, which depends only on the inner or dot product of the input data vectors, it is possible to map the data into high dimensions and still keep the computational cost low. The SVM model depends on a subset of the training samples, known as support vectors, which are used to determine the hyper-plane for classification or regression. Other examples of SVM applications to transportation problems include its use

for traffic speed and traffic flow predictions, and incident detection in the context of ITS applications [15, 17].

C. Integrated Traffic and Communications Simulator

With recent interest in VII, significant effort has been devoted to developing an integrated simulation platform connecting traffic and communications simulators. Earlier work on integrated traffic and communications simulations focused on creating simplified models of communication characteristics [20, 21]. This approach had apparent advantages for fast validation of different traffic operational concepts without too much concern about the details of communication efficiency and reliability. However, it often led to inevitable omissions of fine-grain random effects in the network communications process. On the other hand, several studies have adopted a simplified vehicular movement model (e.g., random way point model) to feed geographic and kinetic data of nodes for detailed communication network modeling [22, 23]. While randomized node movement and message generation models are commonly used by the mobile ad hoc network research community in validating networking protocols for generic applications, they are inadequate for real-time validation of specific vehicular traffic operations. More recently, simulators integrating microscopic traffic and detailed network protocol modes were developed for vehicle-to-vehicle communication [24, 25]. The authors of these papers made a convincing case that an integrated traffic and network simulator revealed important findings that were not otherwise observed. Such simulators either integrate mature simulators from each domain [26, 27] or completely compose both functions to meet study-specific requirements [28, 29]. However, none of these previous studies appears to have addressed communications involving fixed field equipments. Furthermore, no explicit-traffic-explicit-communication simulator that integrated state-of-the-art traffic and communication simulation software has been reported. Among the prevalent modern simulators used for communication studies are Network Simulator version 2 (ns-2) [30], Glomosim [31], Jsim [32], Qualnet [33], and OPNET [34], with ns-2 providing the most comprehensive open source support of communication protocols. In the traffic simulation domain, PARAMICS is a microscopic traffic simulation program that features a flexible Application Programming Interface (API) for customized interface with other programs. In the current study, ns-2 and PARAMICS are adopted to build a simulation platform for detailed communications and traffic modeling, which is necessary for modeling a VII based real time travel time prediction system.

D. Vehicle Infrastructure Integration (VII)

Since 2003, FHWA has sponsored a variety of efforts that led to the development of the national Vehicle Infrastructure Integration (VII) architecture and its functional requirements [35]. Recently, the USDOT has conducted a research program called Mobility Applications for Vehicle Infrastructure Integration initiative [36]. In that program, researchers studied the potential for transmitting information between infrastructure and vehicles to enhance safety and mobility.

Several states including California [37] and Michigan [38] have also tested various methods for implementing these types of programs [39].

For traffic operations applications, VII California [40] demonstrated the efficacy of using VII for online traffic condition assessment. In that demonstration, individual vehicles were used as probe vehicles to send their location, speed, direction, and time stamp to a centralized processing center for traffic surveillance and traveler information dissemination. Crabtree and Stamatiadis [41] and Tanikella et al. [42] illustrated that the travel time data generated from VII can reliably estimate traffic conditions and identify incidents. Moreover, many other studies investigated the potential of VII for road and weather condition assessment [43]. However, none of these studies appear to have used VII for online travel time prediction.

The current study proposes to take advantage of direct traffic measurements available from individual VII-enabled vehicles and state-of-the-art AI algorithm (specifically ANN or SVR) for real-time highway travel time prediction. In this study, the proposed VII-ANN and VII-SVR frameworks were then evaluated in a detailed microscopic simulation environment and their performances were compared against a baseline travel time prediction algorithm.

III. METHODOLOGY

This section discusses the assumptions made and the steps taken to develop and evaluate the proposed VII-ANN and VII-SVR framework for online travel time prediction, using a highway network in Greenville, South Carolina.

A. Basic Assumptions and Proposed Framework

In the selected test network, roadside units (RSUs) with microprocessor and wireless interfaces were assumed to be located at every interchange along the highway. Traffic data collected by the RSUs from VII-enabled vehicles were to be aggregated at a controller where AI (ANN or SVR) algorithms would be running to relate the current traffic condition to the travel time of vehicles departing the start point during the next time step. The authors assumed that each VII-enabled vehicle could communicate with RSUs on approach. The VII system was designed to use information such as time stamp and vehicle location from the individual VII-enabled vehicle to identify such macroscopic traffic measurements as traffic density, flow and segment travel time for the VII-enabled vehicles.

For predicting travel times, six variables were initially selected as candidate predictors of the travel time for the time step under consideration (i.e. the target travel time in Table 1). These were: (1) the measured travel time for the whole highway segment under consideration during the previous time step; (2) the measured junction-to-junction (J2J) travel time (measured from VII-enabled vehicles that completed one junction to another during the previous time step); (3) the density of the VII-enabled vehicles, calculated as the total number of VII-enabled vehicles remaining within the segment divided by the segment length; (4) the entry flow of the VII-

enabled vehicles into the segment during the previous time step; (5) the exit flow of the VII-enabled from the segment during the previous time step; and (6) the change in the VII-enabled density. The J2J travel time was measured first for each VII-enabled vehicle as the difference between the times when it was on the highway and communicated with the RSU at two consecutive interchanges, and then averaged for each J2J segment and summed up for the entire highway segment under consideration.

A correlation analysis was then performed to identify a subset of the six candidate predictors which had the highest correlation with the dependent variable (i.e. the target or predicted travel time for the next time step). As shown in Table 1, the “VII Vehicle Density” was found to have the highest correlation with the target travel time. This is not surprising given the generalized definition of traffic density as the total time spent by all vehicles in the roadway section (with length l) during an observation interval t divided by $l \cdot t$ [44]. Besides “VII Vehicle Density”, “Measured Whole Segment Travel Time” and “Measured J2J Travel Time” appear to be highly correlated to each other, and to the “Target Travel Time”. However, the J2J travel time had a higher correlation to the target travel time compared to the travel time measured over the whole segment. Besides, the J2J travel time has the additional advantage of not only increasing the number of travel time data points that can be collected, but of reducing the prediction horizon in the sense that the input travel time is realized closer to the target travel time as well. Additionally, using J2J travel time is less susceptible to the impact of non-continuous highway trips (i.e. trips that stop in the middle of the trip for some reason) to some extent. In addition to travel times, the “VII Vehicle Exit Flow” had a relatively higher correlation factor compared to the entry flow or density change. Given this, the authors decided to use the following three input variables as predictors: (a) the current junction-to-junction travel time; (b) the VII-enabled vehicles’ density; and (c) the VII-enabled vehicles’ exit flow. All input variables for current time step were measured during the previous time step.

B. The Integrated Simulator

As mentioned above, this study used an integration of the traffic simulator PARAMICS and the network simulator ns-2 to develop and evaluate the VII-ANN and VII-SVR frameworks for travel time prediction. PARAMICS is a time-step, behavior-based microscopic traffic simulation software [45]. In PARAMICS, many different Driver Vehicle Units (DVUs), including VII-enabled vehicles in this research, interact in the simulation model to represent the traffic conditions realistically. A unique feature of the PARAMICS model that made it quite appropriate for this study is its Application Programming Interface (API). API is a PARAMICS add-on module, which allows users to modify many features of the underlying PARAMICS models, as well as connect PARAMICS’s internal modeling core with external customization and software [45]. The ns-2 simulator on the other hand, is an open-source software with an open-source architecture which allows great freedom in incorporating

newly developed protocol components and interfacing with other software [32]. Both the PARAMICS API and ns-2 model are C-based programmable and have open architecture, making it convenient to synchronize and transfer data (i.e., communicate between these two software packages).

In this study, PARAMICS was used to realistically model the traffic flow of the selected test network. Its API was also used to continuously collect traffic measurements, and to synchronize command control and data exchange with ns-2. On the other hand, the real-time vehicle-to-vehicle and vehicle-to-infrastructure communications including addressing, routing, and scheduling solutions were modeled in the ns-2 environment. Specifically, each fixed node in ns-2 corresponds to a VII device (i.e., RSU and controller) and performs different functions such as data collection, exchange, process and dissemination. Each vehicle in PARAMICS is represented as a mobile node in ns-2. An ID is assigned to each vehicle when it enters the network, this ID uniquely identify this vehicle and track its movement throughout its life cycle in the network. Once the vehicle exits the highway network, its ID is recycled to save the run time memory. PARAMICS and ns-2 perform synchronized locked-step executions to model simultaneously the vehicular traffic dynamics and network communications.

Figure 1 shows the execution flow chart that implemented the described integrated simulator scheme. A synchronization file was used to act as a switcher to control the sequential running of PARAMICS and ns-2. During the integrated simulation, both PARAMICS and ns-2 intermittently check the synchronization file to determine whether its counterpart has finished its simulation period. At the beginning of each synchronized period, PARAMICS runs first for one period (e.g., 30 seconds) to update the control file with the mobile nodes (vehicles) movement and messages sending command in TCL language that ns-2 can interpret. Then, ns-2 load and push those events from the control file updated by PARAMICS into its scheduler for execution. Given its role (i.e., RSU and controller), the simulated fixed node in ns-2 collects real time data (i.e. the RSU role), and applies the ANN, SVR or other model for estimating future travel time (i.e. the controller role). If the communicated information involves impacts on traffic dynamics (e.g., display traffic information on variable message sign (VMS) to impact drivers’ behavior), ns-2 will log the specific command into the control file, so that PARAMICS can interpret it and execute it in the next synchronized period. This process continues until the end of the integrated simulation.

1) *Communications Simulation:* The communication networking simulation software ns-2 (version 2.29) simulates various protocols, in each hierarchical layer of the internet architecture, at packet-level, among nodes for a specified network topology. The simulated layers for this study are summarized in Table 2. Network protocols were developed and/or modified with individual source files in C++ to allow for simulating the AI VII travel time prediction system. The corresponding changes in OTCL library and header file were also made. As can be seen in Table 2, user-defined applications, such as the AI travel time prediction algorithms in the controllers, were inserted at the application layer with a function of C++ source codes. UDP-based (UDP stands for

User Datagram Protocol) transport protocol with modified message header and corresponding interpretation scheme was developed to support VII data networking and VII travel time prediction applications. In the network layer, the developed hierarchical message routing scheme at each fixed node was implemented as a new routing agent class with several member functions. Finally, the ns-2 embedded IEEE 802.11p protocols were adopted for the MAC (i.e., Media Access Control) and Physical layer. To start the communication networking simulation, network topology, nodes parameter configuration, simulation initialization and tracking were specified in OTCL language.

As stated in Table 2, the default IEEE 802.11 implementation available in ns-2 (version 2.29) was adopted to articulate IEEE 802.11p MAC and Physical layer. Table 3 presents the standardized MAC and Physical layer parameters included in the ns-2 simulation environment. The only major difference between the simulated and the actual IEEE 802.11p protocol is that the data rate of 54 Mbps, specified by the IEEE 802.11 a/b/g protocol, was used instead of a data rate between 3-27 Mbps, specified by the IEEE 802.11p protocol.

2) *Traffic Simulation:* With PARAMICS, network building began with the collection of field data including geometric, traffic control, and traffic volume data. The network was then calibrated through comparison between the simulated volume output and the field traffic counts data. The calibration process also compared site-collected queue lengths and travel times to those produced by the simulation model. After many iterations and adjustments to the road network and driver behavior parameters, the simulation model was considered to accurately reflect the observed travel times within one percent and no significant difference was observed between the observed and simulated queue lengths at the bottleneck segment. This approach followed similar methodology adopted by other researchers in calibrating and validating microscopic traffic simulation models [46, 47].

With the simulation model developed, the next step was to generate the training and testing cases for the VII-ANN and VII-SVR travel time prediction model. The development and calibration of these two AI algorithm required a set of training cases with the aforementioned three input variables (namely current J2J travel time, VII-enabled vehicles flow and density), and the target output (i.e. the simulation-generated travel time for vehicles departing the start point during the next time step). To do this in PARAMICS, the VII-enabled vehicles were assigned a special vehicle type, with varying percentages relative to the entire traffic population depending on the penetration rate of the VII-enabled vehicles considered. An API program was then developed to log a series of cases or vectors (x_i, y_i) , where y_i is the target travel time and x_i is the input vector that has three afore mentioned member variables. For this study, two minutes were used as the time interval to log x_i 's as inputs for ANN and SVR prediction algorithm.

C. Developing the ANN Model

Given that the target travel time is roughly monotonic with the input variables (e.g. previous travel time, density and flow), and given that the dimension of the input vector is only three, the authors adopted the conventional and widely used

Multi Layer Feed-forward (MLF) neural network with back propagation (BP) learning, for developing the VII-ANN model for online travel time prediction. The MLF neural network in this study consists of one input layer, two hidden layers, and one output layer. The sigmoid functions were used as the transfer functions for the hidden layers and a linear function was used for the output layer. The NeuroSolutions® [48] software was used to determine the number of neurons in the hidden layers, resulting in 10 neurons for the first hidden layer and 5 neurons for the second hidden layer. The training ended either after the number of training epochs exceeded 10,000 or when the cross validation error started to increase. A learning rate equal to 0.01 was used.

D. Developing the SVR Model

For this study, the \mathcal{E} -SVR was adopted. Given a training data set of (x_i, y_i) , $i = 1, \dots, l$ where $x_i \in R^3$ (representing the input vector with three real numbers) and $y_i \in R$ is the target output, the objective of the training by applying \mathcal{E} -SVR is to find the prediction function that optimizes the minimum distance between the regression hyper-plane for any sample of the training data. This can be achieved by solving (1) [49, 50]:

$$\begin{aligned} \min_{w, b, \xi, \xi^*} \quad & \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i + C \sum_{i=1}^l \xi_i^* \\ \text{subject to} \quad & w^T \phi(x_i) + b - y_i \geq \varepsilon - \xi_i \\ & -w^T \phi(x_i) - b + y_i \leq \varepsilon - \xi_i^* \\ & i = 1, \dots, l \text{ and } \xi_i, \xi_i^* \geq 0 \end{aligned} \quad (1)$$

where w , b , ξ , ξ^* are the coefficient, constant, and error term for the SVR prediction function; ε is a parameter in \mathcal{E} -SVR representing the marginal error of regression; ϕ is the transformation function, which mapped the training vectors x_i into a higher dimensional space, enabling the SVR to find a hyper-plane for linear regression with the maximal margin in this higher dimensional space. The support vectors are those (x_i, y_i) whose error terms ξ / ξ^* are not 0. After the training process has identified the support vectors and all the mapping function coefficients and constants, the prediction function for a new input can be expressed as:

$$y = w^T \phi(x) + b \quad (2)$$

Furthermore, the kernel function $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$, determines the form of the transformation function ϕ . In this study, radial basis functions (RBF) were used as the kernel functions for its generally good performance in many scenarios [51].

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0 \quad (3)$$

Here, γ is the kernel parameter.

As noted by [49, 52], scaling is important for the success of AI paradigms such as ANN and SVR. Before training, all the

data were linearly scaled to a range of [0, 1] using a common range file, which was saved and re-used later during the prediction phase. Moreover, to maximize the utility of the training data while searching for the SVR optimal parameters set, the authors randomly divided the training dataset into five groups. Each time, four groups of data were used to train a SVR model with a possible combination of parameters, then the trained model was validated on the remaining group to estimate the prediction accuracy in terms of mean squared error (MSE). This process was repeated five times with the same parameter combination for different training and validating groups, to obtain an average value for the cross-validation prediction accuracy rate. After the optimized parameter combination was identified, the evaluation was performed by applying the trained and validated ANN and SVR model on the testing dataset, which was not used in the training and validation process. The SVR algorithm for the travel time prediction, as described above, was implemented using PARAMICS API, utilizing various functions from LIBSVM [50], a software library for SVM.

E. Evaluation of the VII-ANN and VII-SVR Model

The authors tested different penetration rates to evaluate the effectiveness of the proposed travel time prediction framework. The measures of performance for the VII-AI framework included a frequency plot that gave the percentage of prediction cases falling within a specific range of the relative error between the predicted and the simulated travel time. In addition, four other measures were used to assess the prediction accuracy, namely the: a) root mean of squared error proportional (RMSEP); b) mean relative error (MRE); c) mean absolute relative error (MARE); and d) standard deviation of relative error (SRE). These four measures are defined in (4) through (7), where t_i is the target value of the travel time; y_i is the predicted value; e_i is the prediction error and is equal to $y_i - t_i$; re_i is the relative error equal to e_i / t_i ; and N is the number of experiments.

$$\text{RMSEP in percentage: } \frac{100}{\bar{t}} \sqrt{\frac{1}{N} \sum_{i=1}^N (e_i)^2} \quad \text{with } \bar{t} = \frac{1}{N} \sum_{i=1}^N t_i \quad (4)$$

$$\text{MRE in percentage: } \frac{100}{N} \sum_{i=1}^N re_i \quad (5)$$

$$\text{MARE in percentage: } \frac{100}{N} \sum_{i=1}^N |re_i| \quad (6)$$

$$\text{SRE in percentage: } 100 \sqrt{\frac{1}{N-1} \sum_{i=1}^N (re_i - \text{MRE}/100)^2} \quad (7)$$

In order to provide a baseline algorithm for comparison with the developed intelligent algorithms, a popular and easy-to-implement real-time travel time prediction algorithm, called the instantaneous algorithm [1, 15], was coded and compared with the proposed VII-ANN and VII-SVR model. The comparison was performed on the same network and under the

same traffic conditions. The instantaneous travel time prediction model assumes that the travel time does not change for a short period. Therefore, it only uses the available travel time collected within the immediate previous time step to predict the travel of vehicles that will start within the immediate following time step. Since the VII system is able to collect the travel time directly, the averaged travel time of the VII-enabled vehicles arriving at the end point during each time interval will be considered as the predicted travel time of the vehicles departing the start point during the next time interval for the instantaneous algorithm.

F. Application to Case Study Network

The I-85 corridor in Greenville, South Carolina, was selected as the study site for case design. The network, as can be seen from Figure 2, consists of approximately 11 miles of freeway and 6 interchanges. This section of I-85 is part of the corridor connecting Atlanta, Georgia, and Charlotte, North Carolina. It services the traffic from and to the Greenville metropolitan area with a population of over 600,000 people, according to the 2006 census estimate. Both long-distance traffic (which accounts for about 30 percent of the total traffic volume) and local traffic (which accounts for the remaining 70 percent) have significant impact on the freeway network. While this freeway section is further supported by I-385 (which intersects with I-85 at exit 51) and I-185 (which intersect with I-85 at exit 42), there are no major arterials parallel to I-85 that have the potential to accommodate traffic diversion during congestion.

The prototype travel time prediction system considered in this study predicts travel time along the northbound segment of I-85 between Exit 40 and Exit 51. The free flow travel time for that segment is around 10 minutes. During congestion, it could take more than 20 minutes to traverse the segment. The traffic scenario that this study focused on was the weekday PM peak period. Simulations were started at 4:00 PM and allowed 20 minutes of warm up time. After traffic was fully loaded onto the network (i.e. at 4:20 PM), the travel time prediction system started working and continued until 9:40 PM. Peak traffic flow generally occurred between 4:30 PM and 6:30 PM at the study site.

To generate the training and testing sets, a simulation model with various VII penetration rates (i.e., the percentage of VII-enabled vehicles in the total traffic population), generated the traffic data for a period of four weeks with recurrent congestion along the study segment of I-85 as shown in Figure 2. Among all the cases, two weeks of data were randomly selected as the training data and the remaining two weeks were used for testing for both VII-ANN and VII-SVR models. As mentioned above, the authors collected traffic volumes, travel time, and queue length in the real world, and used it for carefully calibrating the simulation model before generating the training and testing data sets. The simulated traffic conditions (locations and severity of congestions) were also face validated by the experts from Greenville traffic management center. Figure 3 shows the travel time patterns of ten weekdays with five different traffic demand inputs. These demand profiles were derived based upon real-world

observations, and hence should create a reasonably realistic and challenging test environment for testing the accuracy and robustness of VII-AI travel time prediction system. Note that the same traffic demand inputs may result in different travel time patterns due to the random nature of the microscopic traffic simulation model.

IV. PERFORMANCE ANALYSIS

The following sections present the implementation details and evaluation results for the proposed VII-ANN and VII-SVR frameworks. Before evaluation, the parameters of the SVR algorithms were adjusted to achieve optimal performance as described below.

A. Parameter Adjustments for the SVR Algorithm

An important step in developing an SVR algorithm involves determining the optimal parameters for the algorithm. Figure 4 shows the results of the grid search for the three optimal parameters (cost coefficient C , kernel function parameter γ and loss function parameter ϵ). As can be seen, the cost coefficient was varied between 2^0 and 2^8 , the kernel function parameter between 2^{-2} and 2^8 , and the loss function parameter between 2^0 and 2^{10} . Each contour line on this contour map represents a specific combination of C , γ and ϵ that produces the same prediction accuracy in terms of MSE. The contours were used to identify the parameter combination that yielded the highest prediction accuracy. The grid searching program identified the best combination of values as $C=2^8$, $\gamma=2^4$ and $\epsilon=2^6$, which gave a MSE value of 2312 for cross-validation.

B. Communication Performance

As shown in Figure 5, the average number of packets received by the RSU per minute increased linearly as the percentage of VII-enabled vehicles increased. On the other hand, the delivery ratios remained close to 100% rate with little variation, regardless of the penetration rate. This guarantees the reliable operation of the proposed VII system. Additionally, the communication times were confirmed to be tolerable, in the order of millisecond.

Note that this study did not simulate the channel performance degradation due to Doppler effects experienced as a result of vehicular movement on the highway at moderate to high speeds. The theoretical and simulation studies on this issue can be found in various literatures (e.g., [53], [54]).

C. Travel Time Prediction Performance

Figure 6 compares the predictive accuracy of the instantaneous, VII-ANN, and VII-SVR models. As can be seen, for the instantaneous algorithm, only 42.2% of the cases had relative errors in the range of -5% to 5% (indicated by the vertical lines in the figure). For the ANN, this number was higher - 59.7%, whereas it was around 63.0% for the SVR. Given this, the ANN and SVR appear to outperform the instantaneous method, with the SVR slightly outperforming the ANN. This can be further seen from Table 4, where both the VII-ANN and VII-SVR model statistics appear to be

superior to the instantaneous algorithm, based on the selected MOEs such as RMSEP and MARE. Additionally, Table 4 indicates that there was little bias in the prediction for the SVR model, with the MRE value very close to 0. At the same time, the instantaneous model predicted travel times which were overall 2.34% longer than the actual travel time. Also evident in Table 4 is the fact that VII-SVR appears slightly superior to VII-ANN in every aspect of the selected performance measures.

To further appreciate the differences among the predictive accuracy of the different algorithms, Figure 7 and Figure 8 track the performance of the instantaneous and SVR algorithms, respectively, for one specific afternoon peak period with recurrent congestion. As shown in Figure 7, while the instantaneous predictive model worked fine during non-congested conditions, there was a lag between the actual and predicted time during congestion. This is because the instantaneous model suffers from the assumption that travel times do not change over short time intervals, which is obviously not the case during congestion. In contrast, Figure 8 shows that the SVR model was quite capable of accurately predicting travel times during both congested and non-congested conditions.

1) *Impact of Different VII Penetration Rates:* Figure 9 shows the MARE and SRE of the travel time prediction using the VII-SVR model with different penetration rates. As expected, the increase in the number of VII-enabled vehicles positively affects the prediction accuracy and variation. At low penetration rates, the travel time and traffic volume data collected from VII-enabled vehicles (which are treated as a sample of the whole traffic population), become unreliable because the sample size is too small and the deviation of the measurement from the population is too high. As the penetration increases, the accuracy improves. The positive effects, however, tend to diminish as the penetration rates keep increasing. Penetration rates in the range of 20% to 25% of VII-enabled vehicles appear to be quite adequate for yielding accurate and reliable travel time predictions.

2) *Predictive Accuracy during Non-recurrent Congestion:* Many conventional sensor based prediction models face challenges accurately predicting travel times during incidents. To test the ability of the VII-SVR model to predict travel time during incidents, a scenario was considered where an incident blocking two lanes was generated at random locations and with random start times between 4:30 PM and 5:00 PM. For each test scenario, a random blockage time of an incident was also determined based on historical incident data at the study site. Compared to a scenario without incident and with the same traffic demand, the scenario with an incident resulted in extensive non-recurrent congestion. The travel time prediction results are shown in Figure 10, which indicates that the developed VII-SVR model is capable of accurately predicting travel times for both normal traffic (recurrent congestion) conditions and conditions during incidents (non-recurrent congestion). Moreover, Table 5 compares the performance of instantaneous and VII-SVR travel time prediction model for recurrent and non-recurrent congestion conditions. As in the recurrent congestion scenarios, VII-SVR was again superior to

the instantaneous algorithm in the non-recurrent congestion scenarios. As expected, all three algorithms performed better in recurrent congestion scenarios than in non-recurrent congestion scenarios. However, VII-SVR performed reasonably well under incident condition, though it intended to over-estimate the travel time. The VII-ANN model also performed similarly. The capability of predicting travel for non-recurrent congestion for VII-AI framework should be credited to the real-time traffic data available from VII. The inputs to VII-AI framework are similar for recurrent and non-recurrent congestion. Consequently, the proposed framework performs reasonably well for the non-recurrent condition, despite the lack of such training data set.

D. Discussion

This study was conducted in a simulation environment, because a field test is costly, difficult and cannot be conducted before a system is actually deployed. Simulation, on the other hand, provides a cost-effective and efficient alternative. As previously mentioned, the developed simulation models for this study were carefully calibrated and validated to realistically represent the real world, which should increase confidence in the study's conclusions. Though this study demonstrates the potential of a VII-AI framework for travel time prediction using VII-SVR and VII-ANN as one example, other intelligent algorithms such as Genetic Algorithms and Fuzzy Logic may serve as the AI paradigm in the VII-AI framework with similar performance. A common characteristic of many AI paradigms is that the parameter design and calibration is critical for their performances. The results of this case study give a convincing case that careful design and calibration of the AI model can yield powerful travel time prediction systems. Those parameters are expected to be site-specific and should be optimized through a systematic approach to achieve good travel time performance. Additionally, although periodic off-line calibration and adjustment in response to variation in VII-enabled vehicle density and flow is an option, including such VII-AI system into a closed loop framework may be more efficient and would make the system capable of improving its performance over time.

V. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

This paper presented an online highway travel time prediction framework, which used VII with AI (i.e. ANN or SVR) algorithms. To facilitate the design and evaluation of such a framework, this study developed an integrated traffic and communication simulator using PARAMICS and ns-2. A case study involving a freeway network in Greenville, South Carolina was then conducted. From a communications standpoint, the performance of the evaluated ad hoc network for VII system is satisfactory as the delivery ratio was maintained at a very high level (99.95%) and varied little for all experimental scenarios tested in this study. The latency of transmitting messages between vehicles and RSUs was small enough to be considered negligible. From a traffic standpoint,

the evaluation of the VII-ANN and VII-SVR model revealed that the VII-AI algorithms successfully predicted the travel time based on traffic measurements derived from the VII-enabled vehicles. In addition, the developed travel time prediction models outperformed the instantaneous algorithm, which was used as a base-line. When the percentage of VII-enabled vehicles was as low as 20%, the accuracy of the VII-ANN and VII-SVR models, in terms of MARE, were among the best of the reported results in the literature. The study also found that, as expected, increasing the penetration rate of VII-enabled vehicles had a positive impact on the accuracy and variation of the travel time prediction. However, the extra benefits diminish as the proportion of VII-enabled vehicles approached values greater than 25%. Additionally, unlike other sensor based models, the proposed VII-ANN and VII-SVR model performed quite well during non-recurrent congestion conditions.

It should be noted that the integrated traffic and communications simulator which was developed in this research can be quite useful for various interdisciplinary ITS (e.g., VII) research studies. Traffic engineers can flexibly implement and test various advanced ITS technologies such as incident detection algorithms, distributed decision making, and real-time traffic management methods in PARAMICS, while wireless network researchers can evaluate different communication protocols and network parameters in ns-2.

B. Recommendations

Though the results of this research are quite encouraging, there are several potential limitations that warrant the attention of future researchers and practitioners. Foremost, one must keep in mind that evaluation of the proposed framework was conducted mainly in a simulation environment. In a real-world implementation, the performance of the models developed in this study may vary due to factors not considered in a computer simulation. Secondly, the performance of the proposed VII framework was found to be quite sensitive to the penetration rate of the VII-enabled vehicles. Future research should include experiments that would vary the percentage of the VII-enabled vehicles in the traffic population from time to time. Additionally, further study should be conducted regarding the online learning ability of the VII-AI framework and how this could be utilized to improve its performance over time. Although the communication network was found not to be the bottleneck in this study, as VII matures, the communication network may be expected to become congested due to the increased data traffic from many different VII applications (e.g., crash avoidance, curvature warning, adverse road surface and weather condition warning, user data flow, commercial advertisement). Therefore, detailed analysis of the communication system, with appropriate consideration of different communication technologies that support the information exchange between vehicles and infrastructure devices in the VII system, may be required to fulfill the requirements of a real-world implementation.

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Table 1. Correlation Analysis for Travel Time Prediction

	Target Travel Time	Measured Whole Segment Travel Time ¹	Measured J2J Travel Time ²	VII Vehicle Density	VII Vehicle Enter Flow	VII Vehicle Exit Flow	VII Vehicle Density Change
Target Travel Time	1.00						
Measured Whole Segment Travel Time ¹	0.78	1.00					
Measured J2J Travel Time ²	0.91	0.95	1.00				
VII Vehicle Density	0.97	0.78	0.89	1.00			
VII Vehicle Enter Flow	0.39	0.05	0.18	0.49	1.00		
VII Vehicle Exit Flow	0.48	0.33	0.37	0.47	0.32	1.00	
VII Vehicle Density Change	0.00	-0.20	-0.11	0.11	0.70	-0.45	1.00

Note: 1. “Measured Whole Segment Travel Time” represents the measured average travel time from VII-enabled vehicles that completed the entire study highway segment;

2. “Measured J2J Travel Time” represents the sum of the average travel time for each junction-to-junction section of the study highway segment. The travel times were collected from VII-enabled vehicles that completed the part of the trip from one junction to the next.

Table 2. Simulated Protocol Hierarchy Stack

Layer	Protocol	Implementati on	Remark
Application	VII	Customized	Implement VII travel time prediction application
Transport	UDP	Embedded / Customized	Modify UDP protocol to support VII application
Network	IP & VII Routing	Embedded / Customized	Add VII routing protocols to support hierarchal routing
MAC + Physical	IEEE 802.11	Embedded	Configure for different bandwidth and range for wireless communication

Table 3. MAC and Physical Layer Parameter Values

Layer	Parameter	Value
MAC	Minimum Contention Window for congestion control	3
	Maximum Contention Window for congestion control	1023
	Slot Time	20 μ s
	Short Inter-Frame Space	10 μ s
	Retry limit for short MAC Layer frames	7
	Retry limit for long MAC Layer frames	4
	Threshold Limit between Short and Long frames	0 bits
	Header Length	48 bits
Physical	Transmission Range	1000 m
	Wireless Interface Sensitivity	-75 dBm
	Wireless Interface Capture Threshold	-65 dBm
	Transmission Power	25 dBm
	Data rate	54 Mbps
	Noise Floor (for 10 MHz bandwidth)	-99 dBm
	Channel (Physical Medium)	Wireless
	Bandwidth	10 MHz

Table 4. Performance of VII-AI and Instantaneous Travel Time Prediction Models

Model	RMSEP	MRE	MARE	SRE
ANN	6.93%	-0.71%	3.99%	6.80%
SVR	6.73%	0.11%	3.86%	5.38%
Instantaneous	15.56%	2.34%	8.40%	11.37%

Table 5. Performance of VII Travel Time Prediction Models for Recurrent and Non-Recurrent Congestion

Scenario	RMSEP	MRE	MARE	SRE
VII-SVR in Recurrent Congestion	6.73%	0.11%	3.86%	5.38%
VII-SVR in Non-Recurrent Congestion	14.94%	3.04%	8.68%	11.61%
Instantaneous in Recurrent Congestion	15.56%	2.34%	8.40%	11.37%
Instantaneous in Non-Recurrent Congestion	24.76%	2.98%	12.52%	16.66%

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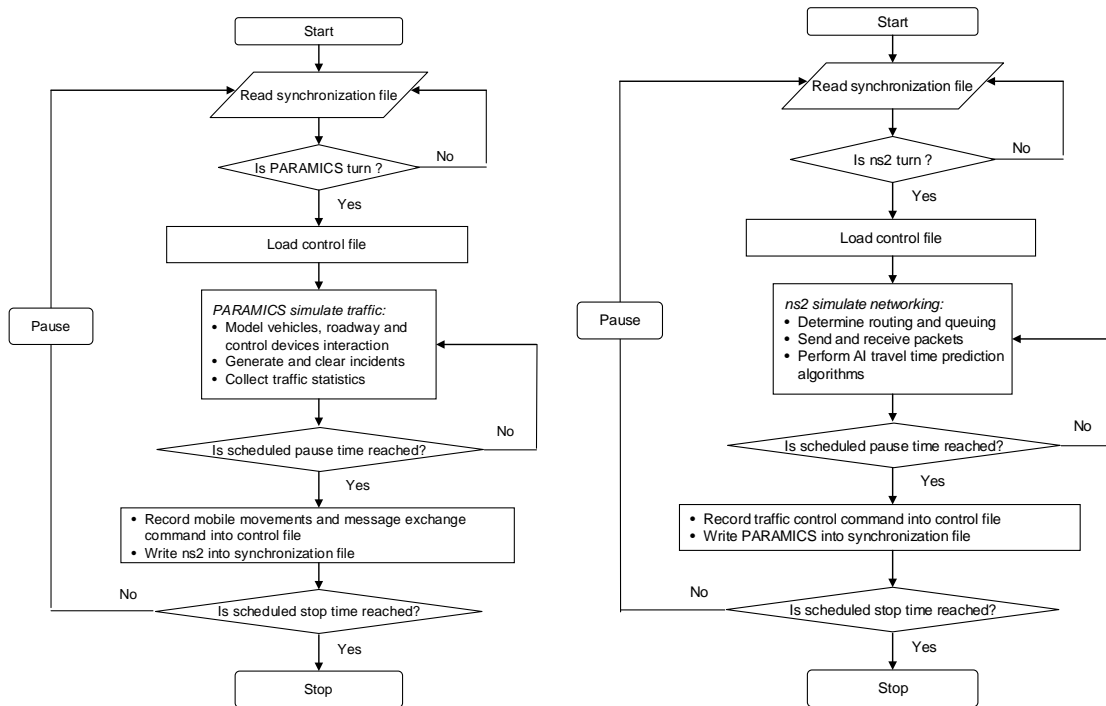


Figure 1. Integrated simulator process execution flow chart

Freeway Network in Greenville, South Carolina

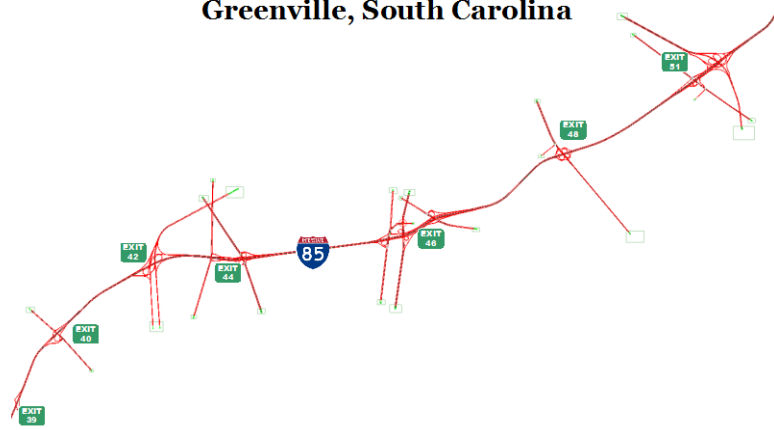


Figure 2. Test network in Greenville, South Carolina

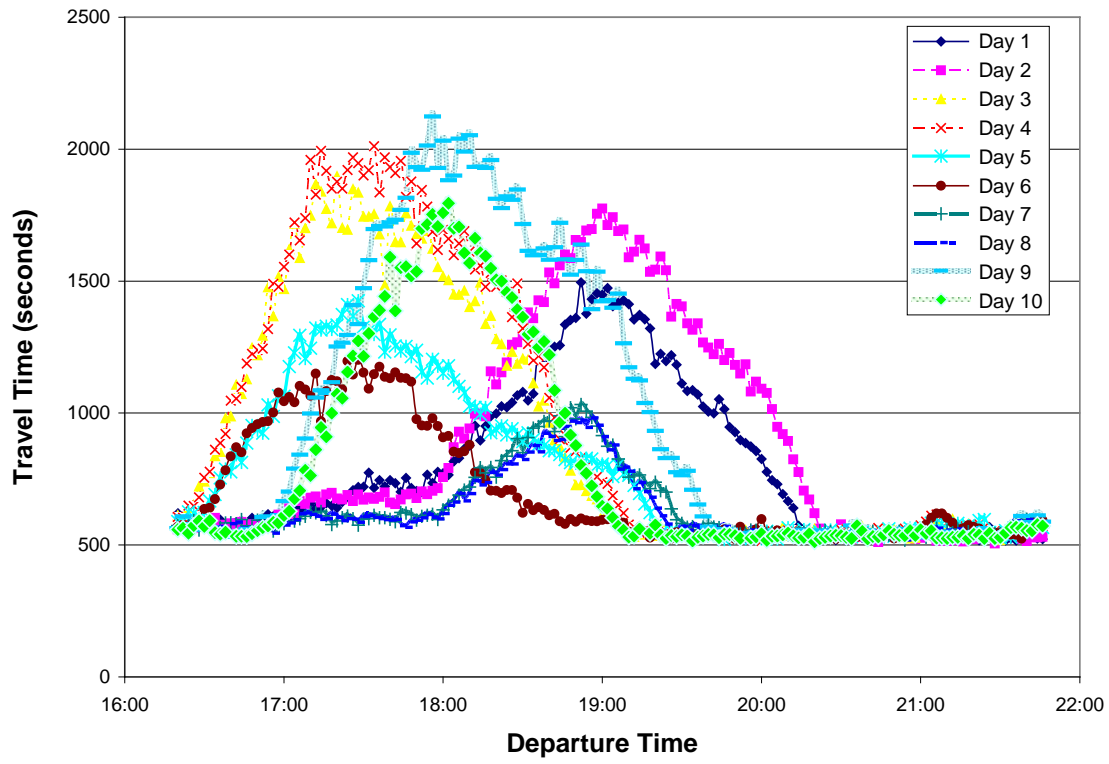


Figure 3. Travel time pattern with different demand inputs

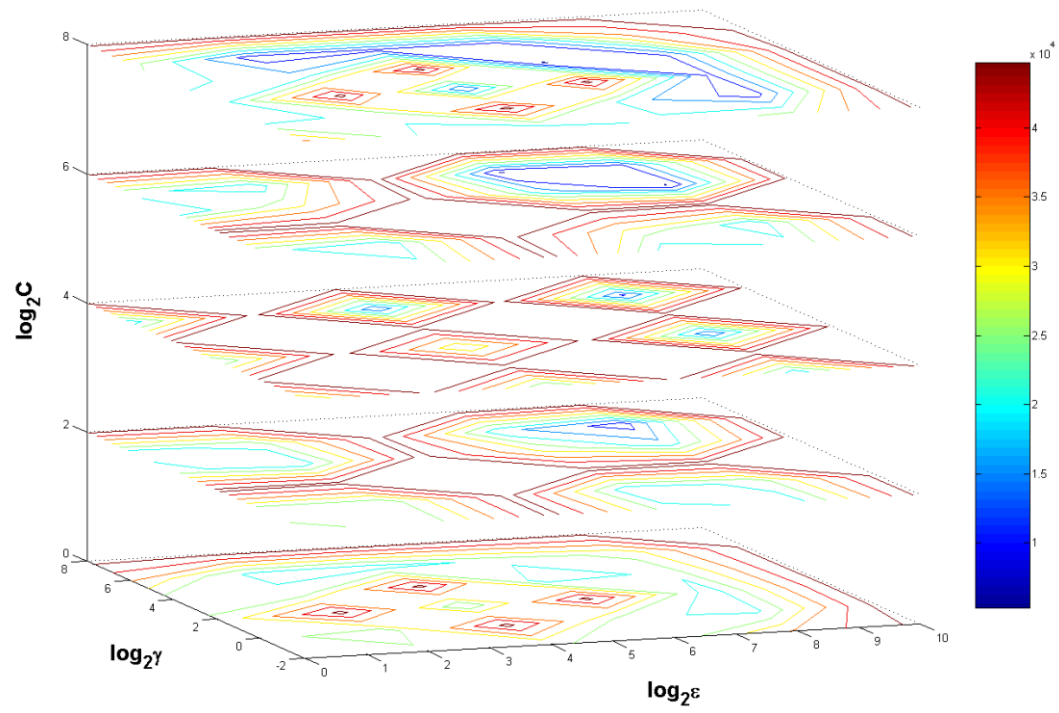


Figure 4. Prediction accuracy (in terms of MSE) contour of parameters combination for developed SVR algorithm

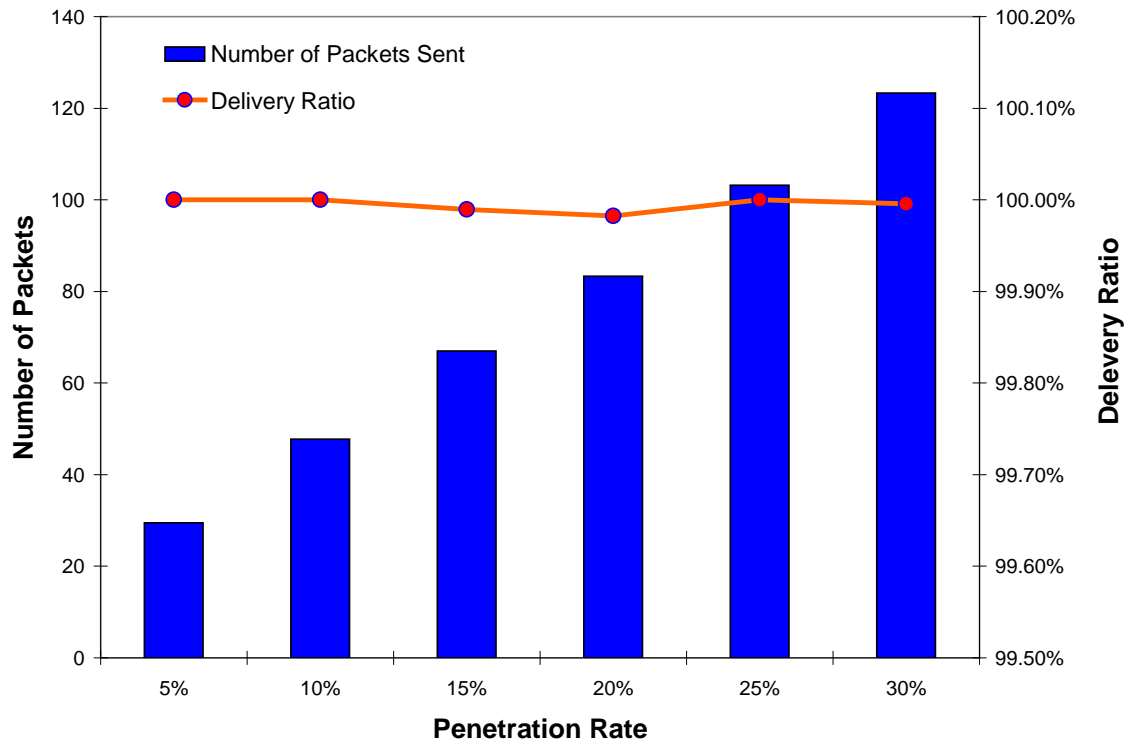


Figure 5. Number of packets received and the delivery ratio of the VII model with various penetration rates of VII-enabled vehicles

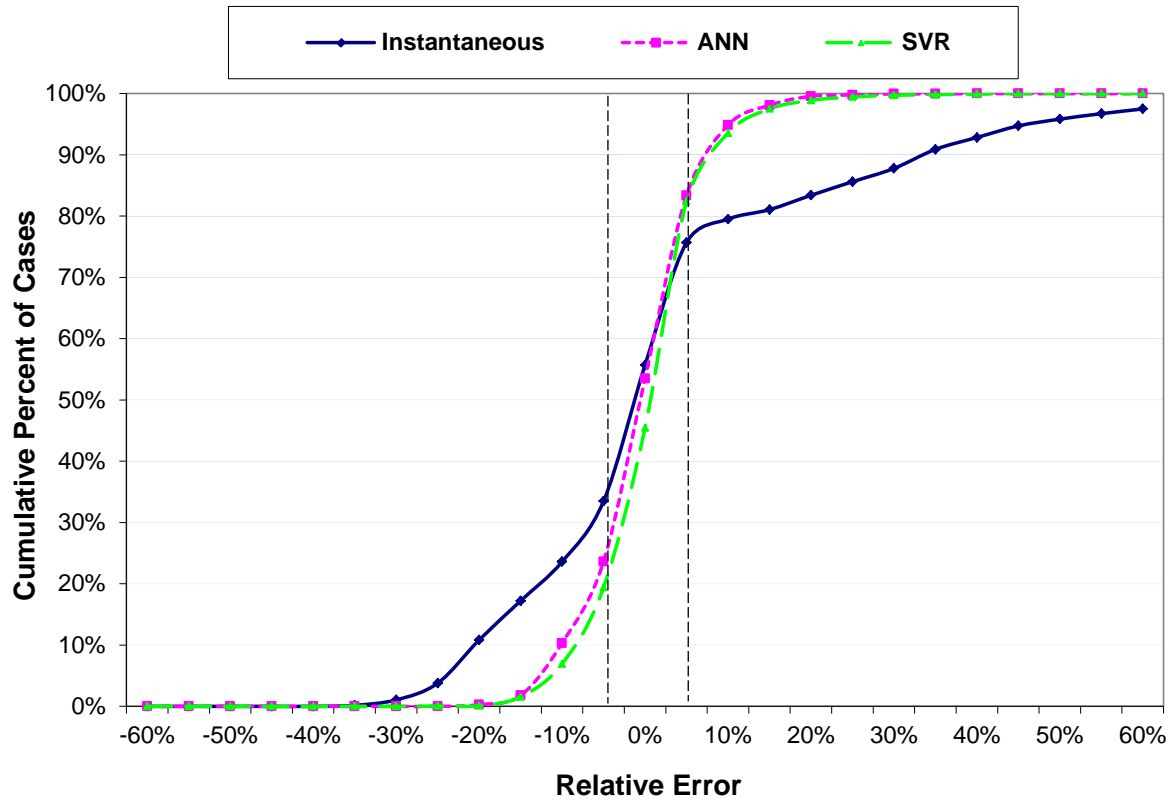


Figure 6. Categorized relative error percentage of different travel time prediction method

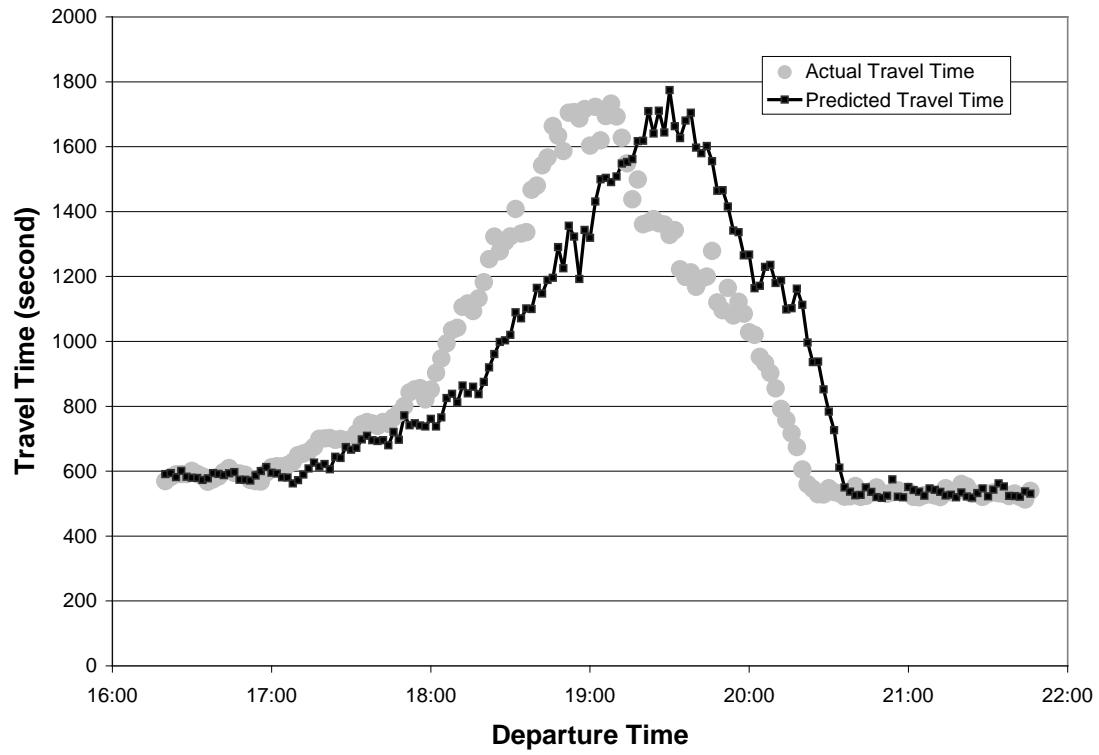


Figure 7. Travel time prediction using instantaneous prediction model

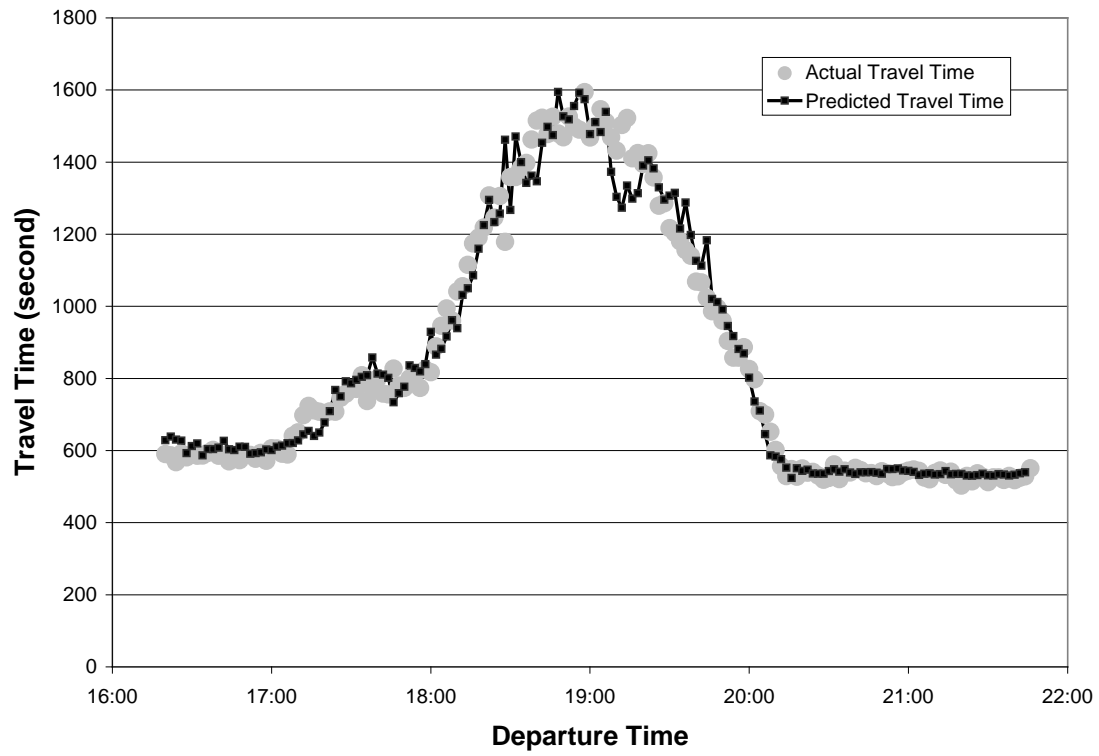


Figure 8. VII-SVR travel time prediction on an afternoon peak period with recurrent congestion

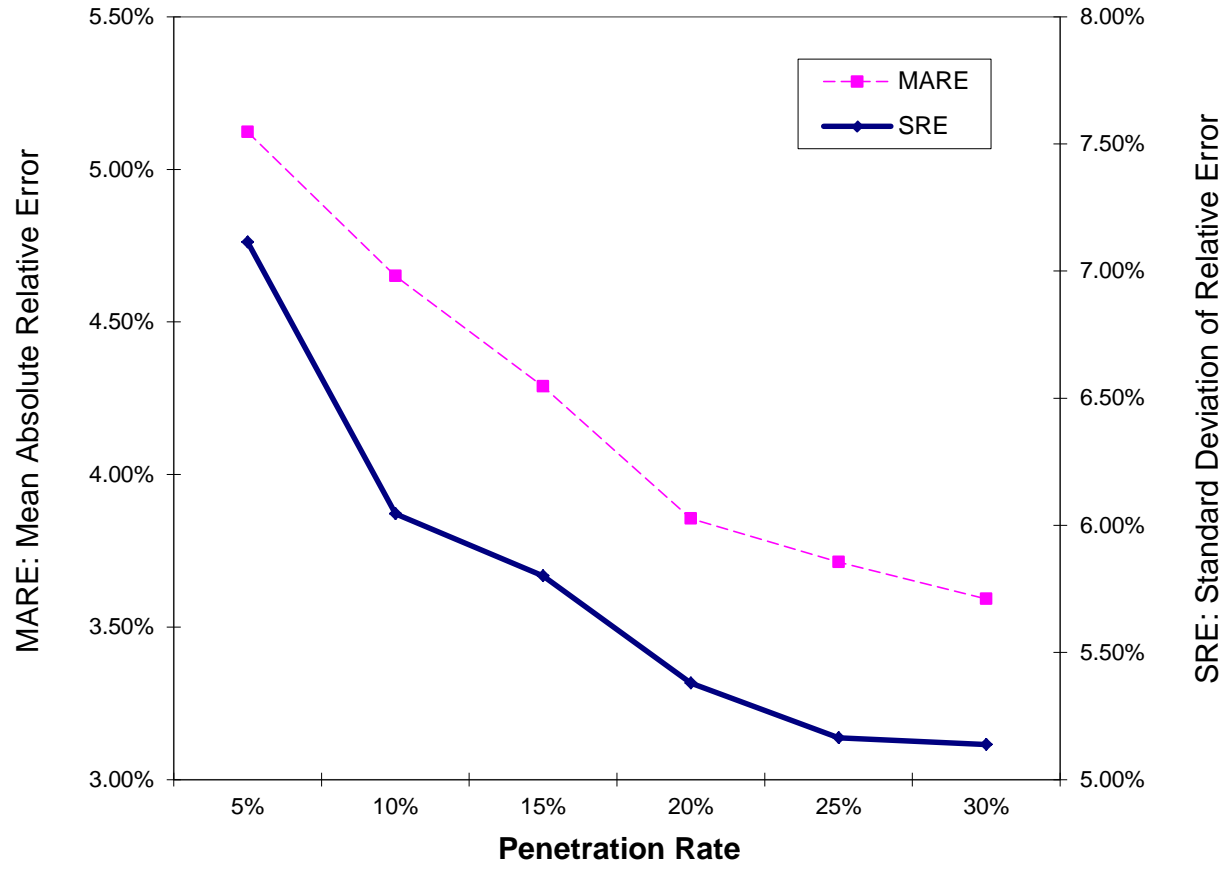


Figure 9. MARE and SRE of travel time prediction with different penetration rates

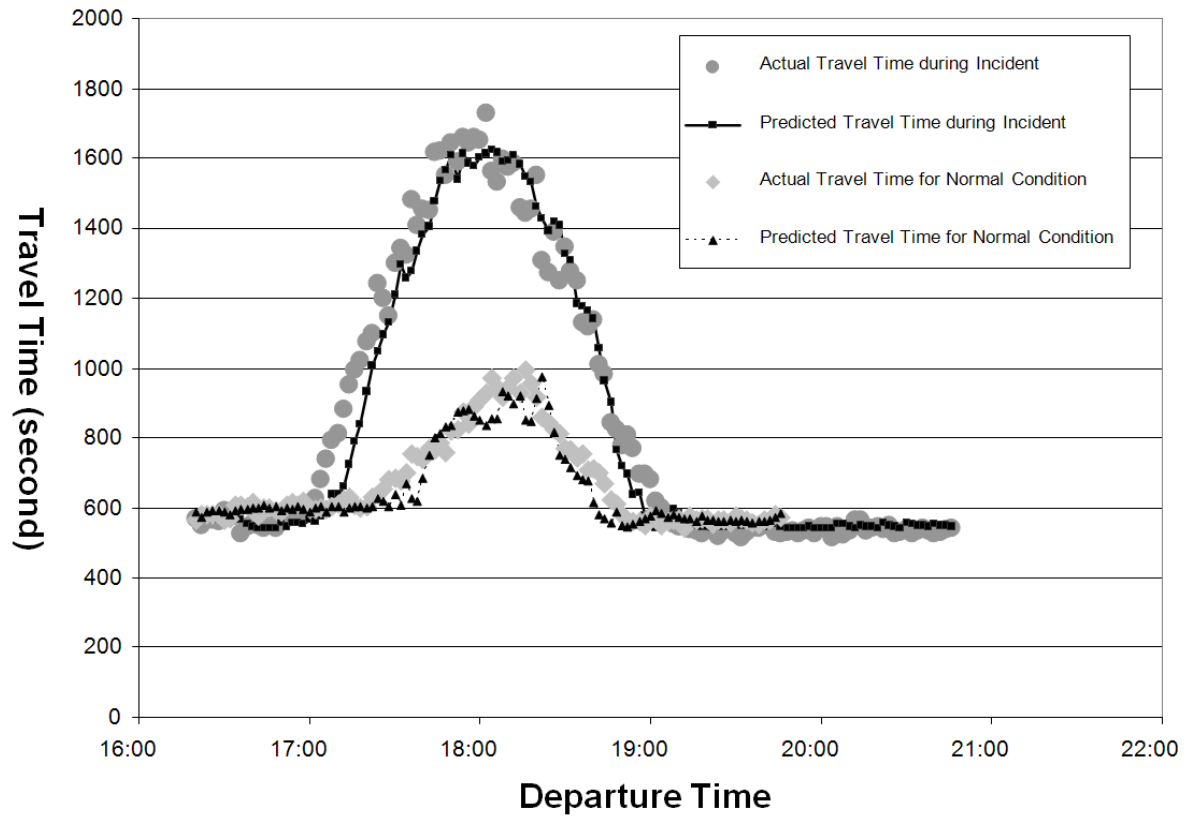


Figure 10. Travel time prediction in both normal traffic conditions and during incident

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